Coherent Breathing Biofeedback: Enhancing Stress Management through Wearable Technology

Tulasi Sainath Polisetty, Ahlada Ruthwik Chakravarthula, Jay B Menon,
Manish Kumar Peteri, Tejaswini Ashok Walunjkar
School of Manufacturing Systems and Networks
Arizona State University, Tempe, USA

Dr. Sari Roth-Roemer
Barrow Neurological Institute
Phoenix, USA

***Abstract*—This study explores the physiological and psychological benefits of coherent breathing facilitated by a novel wearable device, the Balance Bracelet, which utilizes a 6-second inhalation and exhalation cycle to optimize synchronization between Heart Rate Variability (HRV) and Respiratory Rate (RR). Employing advanced Photoplethysmography (PPG) sensors, the device enables real-time monitoring and feedback, enhancing autonomic nervous system balance and promoting emotional stability. Preliminary results indicate that regular practice of coherent breathing significantly aligns HRV and RR, reducing stress responses and improving mental health outcomes. The findings underscore the efficacy of integrating controlled breathing techniques with wearable technology to support daily wellness and resilience against stress, offering significant implications for both individuals and clinical practices. This study not only contributes to the understanding of biofeedback mechanisms in stress management but also highlights the transformative potential of wearable health technology in enhancing life quality.**

Clinical Relevance—This study highlights the potential of coherent breathing, facilitated by a wearable device, in enhancing heart rate variability and respiratory synchronization. The Balance Bracelet could offer clinicians a non-pharmacological tool to assist patients in managing stress and improving cardiovascular health. Regular use of this technique could lead to better outcomes in patients suffering from stress-related disorders, making it a valuable addition to therapeutic strategies.

***Index Terms*—coherent breathing, biofeedback, wearable technology, stress management, heart rate variability, PPG sensors.**

I. Introduction

In an era where mental health and stress management are increasingly crucial, the need for effective, accessible interventions is more pressing than ever. With the rapid pace of modern life fueling anxiety and stress, individuals are often left managing a continuous activation of their sympathetic nervous system. This can lead to a cascade of health issues, including sleep disturbances, impaired cognitive function, and a diminished quality of life. Despite the clear need, many existing solutions either lack ease of use or are financially out of reach for those most in need of stress management tools.

Recognizing this gap, our project introduces the Balance Bracelet, a device designed to foster mental well-being through coherent breathing—a method proven to harmonize the autonomic nervous system and enhance physiological balance. This technique, which involves synchronized breath and heart rates, has been shown to not only elevate heart rate variability and respiratory sinus arrhythmia but also to improve overall psychological health and emotional stability. The benefits extend to visible changes in brain activity, observable through EEG patterns and fMRI scans, and a reduction in common stress symptoms such as anxiety and depression.

Current research, including a notable study by [1], underscores the potential of coherent breathing in significantly enhance psychological well-being, particularly in individuals with major depressive disorder when combined with practices like Iyengar yoga. However, the widespread adoption of coherent breathing has been hindered by a lack of user-friendly and affordable tools. The Balance Bracelet aims to bridge this gap. It is engineered to be cost-effective and straightforward, suitable for users of all technological backgrounds, and designed to be non-intrusive and comfortable for various skin types. By offering real-time feedback on achieving coherence, the Balance Bracelet not only enhances individual practice but also promotes a broader acceptance and integration of this powerful stress management technique into daily routines.

Our approach emphasizes simplicity and accessibility, ensuring that the benefits of coherent breathing are available to everyone. By syncing heart rate and breath rate, the Balance Bracelet provides a practical method to improve overall well-being and reduce stress, making effective stress management a reachable goal for a diverse population.

II. Background

A. The Condition: Modern Stress Challenges

Modern life frequently triggers stress, leading to various health issues. The American Psychological Association's "Stress in America™ 2023" survey highlights the persistence of stress post-COVID-19, with notable health impacts, especially among adults aged 35 to 44 [2]. Stress affects both mental and physical health, causing issues like cognitive impairments and cardiovascular problems due to the overactivation of the sympathetic nervous system. This overactivation leads to a range of stress-related disorders, impacting daily functioning and quality of life [3].

B. Current Treatment Approaches

Current stress management strategies range from pharmacological solutions to lifestyle changes and psychological therapies. Breathwork emerges as a potent, non-pharmacological method to mitigate stress. Controlled breathing significantly reduces symptoms of stress, anxiety, and depression by promoting autonomic balance and enhancing heart rate variability (HRV) [4], [5]. These benefits are particularly significant as they highlight breathwork's ability to influence the autonomic nervous system, providing a simple yet effective tool for stress management [6].

C. Technological Innovations in Stress Management

The integration of technology into stress management, particularly through wearable devices, offers new avenues for personalized health monitoring. Technologies such as the HeartRate+ Coherence PRO app and the Somnox Sleep Robot represent significant advancements, using methods like photoplethysmography (PPG) and responsive feedback to promote relaxation and improved sleep patterns [7], [8]. These technologies exemplify the application of advanced sensor and feedback mechanisms that cater to individual user needs, enhancing the accessibility and effectiveness of stress management tools.

D. Challenges and Implications for Public Health

Despite the benefits of breathwork, its widespread adoption is hindered by factors like the lack of accessible tools and general awareness. These include limited access to trained instructors, lack of public awareness, and difficulty integrating these practices into daily life [9]. Moreover, societal, and personal barriers often hinder individuals from seeking out or sticking to stress management strategies. Overcoming these barriers could significantly enhance public health outcomes by reducing stress-related illnesses and healthcare costs [10]. Effective, accessible interventions like the Balance Bracelet, which promotes coherent breathing, could play a crucial role in public health strategies.

E. Innovative Solutions: The Balance Bracelet

Addressing the need for accessible stress management tools, the Balance Bracelet guides users through coherent breathing to achieve physiological balance. It combines the simplicity of use with advanced sensor technology to measure HRV and provide feedback, making stress management accessible to a broader audience [11]. The device's potential to improve mental and physical well-being aligns with ongoing research and offers a practical solution for everyday stress management. This alignment with user needs highlights the device's potential to serve as a bridge between traditional stress management techniques and modern technological advancements [12].

III. Related Work

The advancement of wearable technologies for stress management and health monitoring has proliferated in recent years, driven by the increasing demand for personal health management tools. This section reviews several key technologies and devices that are pertinent to our project's focus on developing an innovative coherent breathing device. Each reviewed technology has been selected based on its relevance to monitoring heart rate variability (HRV), and respiratory patterns, or providing biofeedback for stress management.

A. HeartRate+ Coherence PRO App

Developed to enhance user wellness through guided breathing exercises, this app utilizes photoplethysmography (PPG) sensors to provide biofeedback related to HRV. Its advantages lie in its user-friendly interface and real-time feedback, promoting relaxation and stress reduction [7].

B. RESPA: Breathing Sensor for Workouts

RESPA focuses on optimizing breathing patterns during physical activities, offering real-time monitoring and feedback to enhance workout efficiency and reduce stress. Its wearable design ensures ease of use during various activities [13].

C. Somnox Sleep Robot

This device is designed to improve sleep quality through controlled breathing techniques and has been clinically tested to demonstrate its efficacy in enhancing relaxation and reducing stress before sleep [8].

D. Oura Ring

A compact and stylish ring that monitors a wide range of physiological parameters, including HRV. It provides insights into sleep patterns, activity levels, and overall health, making it a valuable tool for stress management and wellness monitoring [14].

E. Garmin Fitness Wearables

Garmin's wearables incorporate advanced sensors to track respiration rates and HRV, providing users with detailed health analytics. These devices are particularly noted for their integration of health monitoring with daily activity tracking [15].

F. Breeze: Smartphone-based Biofeedback System

This application leverages the smartphone's microphone to detect breathing patterns and provides gamified elements to encourage regular practice of controlled breathing, which is crucial for managing stress effectively [16].

G. Innovations and Implications

The reviewed technologies highlight the importance of integrating real-time monitoring and feedback in wearable devices to effectively manage stress and enhance user well-being. They also underscore the need for devices like the proposed Balance Bracelet to incorporate seamless integration into daily life, ensuring that they are not only functional but also conducive to long-term user engagement and satisfaction.

Future work in this field should focus on enhancing the accuracy and reliability of physiological monitoring under various conditions, improving user interfaces to support easier integration into daily routines, and expanding device capabilities to include more personalized feedback mechanisms. The ultimate goal is to develop a coherent breathing device that not only supports stress reduction but also promotes a deeper connection with one's physiological state, contributing to overall health and well-being.

IV. Proposed Approach

Our team explored several innovative ideas to enhance stress management through wearable technology, focusing on user-friendly solutions that integrate seamlessly into daily life. After extensive brainstorming, we considered the following options:

1) **Smart Band for the Wrist**: A device equipped with sensors to monitor heart rate variability (HRV) and guide breathing.
2) **Ear Plugs**: Intelligent earplugs designed to block out stress-inducing noise and provide audio cues for breathing.
3) **Finger Cap Sensor**: A fingertip device for measuring pulse and oxygenation to assist with breathing exercises.
4) **Necklace Pendant**: A discreet wearable that tracks respiration and heart rate, signaling engagement in coherent breathing.
5) **Yoga Mat**: An interactive mat with built-in sensors to guide users through yoga and breathing routines.

After careful consideration, we selected the **Smart Band for the Wrist** as our top choice. The reasons for this decision include:

- **Sensor Selection & Placement**: We chose non-intrusive, wearable sensors for continuous monitoring. The wrist provides an ideal location for accurate data collection without discomfort.
- **Feedback Mechanism**: The design incorporates haptic feedback, which, combined with a mobile app, offers visual and auditory cues to enhance the user experience. This makes coherent breathing practices more accessible and engaging.
- **Innovative Design Concepts**: The stylish and functional bracelet design includes built-in HRV and respiratory rate tracking. It integrates into daily routines, allowing users to manage stress effectively without disruption.
- **Data Integration & User Experience**: The intuitive user interface facilitates easy tracking of progress and understanding of physiological states. Features for data logging and analysis will provide personalized health insights.

Our dynamic ideation process led us to focus on developing the Smart Band for the Wrist. This decision underscores our commitment to creating a device that not only promotes coherent breathing but also enhances overall user-friendliness and effectiveness in stress management. We are enthusiastic about moving forward with this concept and developing a prototype that positively impacts stress management and health.

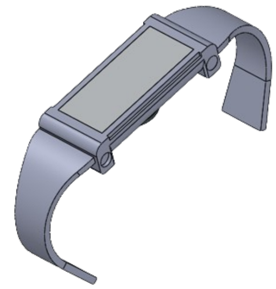

Fig. 1. CAD model for the Prototype

V. Implementation

A. Hardware Design

Our project employs the Arduino Mega, renowned for its enhanced memory capacity and extensive input/output interfaces, making it ideal for handling complex tasks. The hardware configuration includes two Gravity PPG sensors, each serving a distinct function—one for Heart Rate Variability (HRV) and the other for Heart Rate (HR) monitoring. This dual-sensor approach allows for the simultaneous acquisition of HRV and HR, key indicators of physiological stress response and cardiac health. For an in-depth understanding of PPG sensors and their application in clinical physiological measurement, refer to [17].

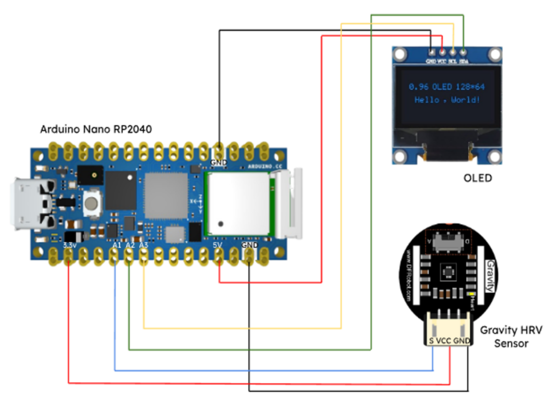

Fig. 2. Hardware circuit design

B. Software Design

The software system for the Balance Bracelet consists of several components that interact to process, analyze, and visualize physiological data from the users. This section provides an overview of the software architecture including data collection, data logging, signal processing, and visualization.

1) Arduino Code for Data Collection: The Arduino Mega is programmed to handle the input from two Gravity PPG sensors, collecting data on Heart Rate Variability (HRV) and

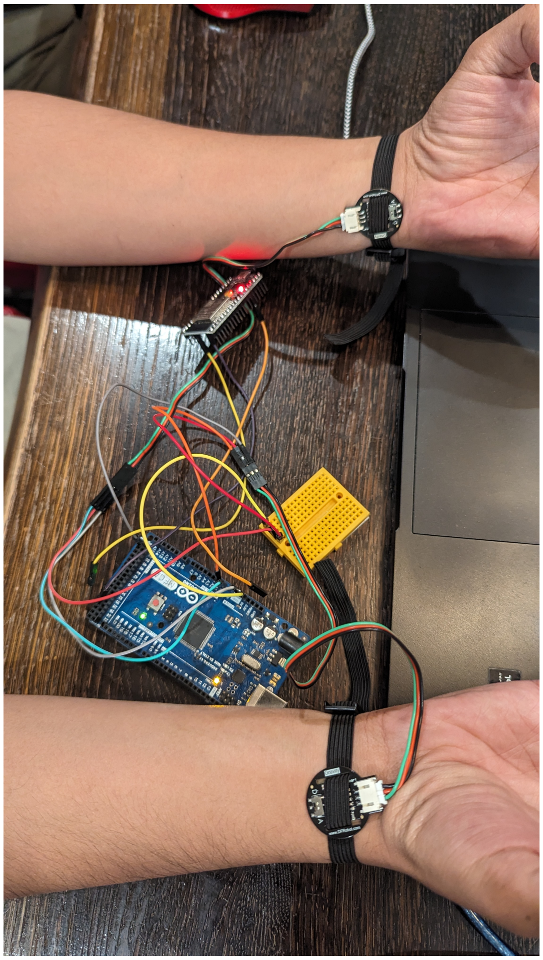

Fig. 3. Arduino Mega and PPG Sensors Setup.

Heart Rate (HR). The software reads analog signals from designated pins configured for each sensor. Data points, each consisting of a timestamp, HRV, and HR values, are formatted into a comma-separated value (CSV-like) structure and transmitted over the serial port. This setup facilitates real-time data acquisition essential for continuous monitoring.

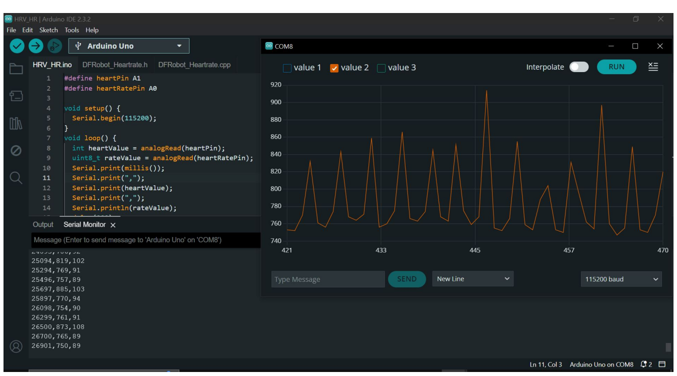

Fig. 4. Heart variability and Heart Rate data collection process

2) Python Serial Data Logging: A dedicated Python script runs on a host computer connected to the Arduino via a serial port. This script listens for incoming serial data in the CSV-like format transmitted by the Arduino. Upon receipt, the script parses the data and stores it in a CSV file for further processing. The logging script remains active, collecting data until manually terminated, ensuring comprehensive session tracking.

3) FFT and Respiratory Rate Calculation: Another critical component of our software architecture is the Python script responsible for analyzing the stored HRV data. The script reads the HRV time series from the CSV file and applies a Fast Fourier Transform (FFT) to transform the data into the frequency domain. This transformation is pivotal for identifying the frequency components that correspond to the respiratory rate.

- **Peak Detection:** The script identifies peaks within the respiratory rate frequency band (typically between 0.1 Hz and 0.4 Hz), which correspond to the dominant breathing patterns of the user.
- **Respiratory Rate Calculation:** From the identified peaks, the respiratory rate is calculated and expressed in breaths per minute, providing a quantitative measure of the user's breathing rate.
- **Visualization:** Additionally, the script includes functionality to plot the respiratory rate over time, offering a visual representation of breathing patterns throughout the data collection period. This feature aids in both user feedback and further analysis by healthcare professionals.

These software components are designed to be modular and scalable, allowing for easy updates and integration with additional sensors or analytic tools as the project evolves.

C. Signal Processing

Signal processing commences with the application of Fast Fourier Transform (FFT) on the time-domain HRV signal, converting it to the frequency domain. Subsequently, a band-pass filter, with a passband specifically tailored to respiratory sinus arrhythmia (RSA), isolates the frequency component correlated to the breathing rate (BR). Identifying the RSA-related peak in the HRV spectrum provides us with the user's respiratory rate (RR). This process involves pinpointing the frequency band associated with the user's normal breathing pattern and extracting the RR from the HRV data by locating the most pronounced peaks within this band. For foundational theories and applications of FFT in signal processing, see [18].

D. Data Features and Model Architecture

The model employed in our study is a 1D Convolutional Neural Network (CNN), optimized for real-time deployment on low-power microcontrollers. This model classifies stress levels based on a variety of input features derived from the SWELL dataset [19]. These features, which capture various aspects of heart rate variability (HRV), are crucial for assessing the autonomic nervous system's response to stress.

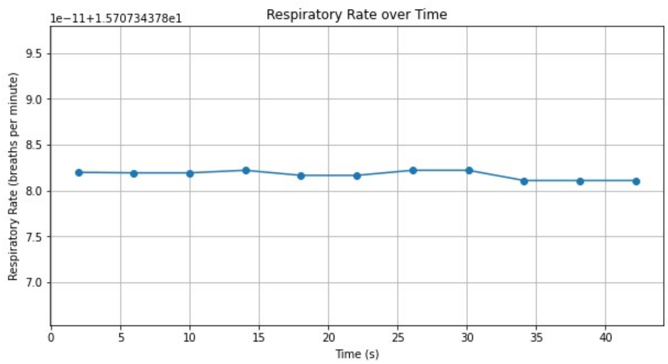

Fig. 5. Peak-to-Peak data plotting of Respiration Rate.

1) HRV Metrics Explained: The HRV metrics used in our model are explained below, providing insights into their significance in physiological stress assessment:

- **Mean RR (MEAN_RR)**: The average time interval between consecutive heartbeats.
- **Median RR (MEDIAN_RR)**: The median time interval between consecutive heartbeats.
- **Standard Deviation of RR intervals (SDRR)**: Measures the variability in time between heartbeats.
- **Root Mean Square of Successive Differences (RMSSD)**: Reflects the beat-to-beat variability in heart rate.
- **Standard Deviation of Successive Differences (SDSD)**: Variability in successive differences between heartbeats.
- **Ratio of SDRR to RMSSD (SDRR_RMSSD)**: A comparative measure of long-term vs. short-term variability.
- **Heart Rate (HR)**: The number of heartbeats per minute.
- **Percentage of RR intervals differing by more than 25 ms (pNN25)** and **more than 50 ms (pNN50)**: Indicators of heart rate variability.
- **Standard deviation of instantaneous (SD1) and continuous (SD2) RR interval variability**: Metrics for assessing complex patterns in heart rate dynamics.
- **Kurtosis (KURT)** and **Skewness (SKEW)**: Statistical measures that describe the shape of the distribution of RR intervals.
- **Relative metrics (MEAN_REL_RR, MEDIAN_REL_RR, etc.)**: These are calculated similar to their absolute counterparts but normalized against baseline measurements.
- **Very Low Frequency (VLF)**, **Low Frequency (LF)**, and **High Frequency (HF)** components: Spectral components of HRV that relate to different physiological mechanisms.
- **Total Power (TP)** and frequency ratios (**LF_HF**, **HF_LF**): Overall HRV and balance between sympathetic and parasympathetic nervous activity.
- **Sample Entropy (sampen)**: Measures the regularity and complexity of a time series.
- **Higuchi's Fractal Dimension (higuci)**: Quantifies the fractal dimension of HRV, indicating the complexity of physiological time series data.

These metrics collectively offer a nuanced view of an individual's physiological state under stress, serving as the input features for our CNN model. The output variable, denoted as **Y**, categorizes the condition under which the data was recorded, such as "no stress," "time pressure," or "interruption," which are critical for contextual analysis in stress response studies.

The architecture of the 1D CNN model is outlined in Table I, which details the function and dimensionality of each layer, underscoring its role in feature extraction and classification.

TABLE I
1D CNN MODEL ARCHITECTURE

Layer (type)	Output Shape	Param #
Conv1D	(None, 62, 64)	256
MaxPooling1D	(None, 31, 64)	0
Conv1D	(None, 29, 128)	24704
MaxPooling1D	(None, 14, 128)	0
Flatten	(None, 1792)	0
Dense	(None, 64)	114752
Dropout	(None, 64)	0
Dense	(None, num_classes)	650

E. Model Training

The model is trained using the Adam optimizer, with a loss function designed for categorical outcomes. Training parameters are chosen to balance computational efficiency and model performance:

- Optimizer: Adam
- Loss Function: Categorical Crossentropy
- Batch Size: 32
- Epochs: 100
- Validation Split: 20%

The model demonstrates robust performance with high train and test accuracies, and an impressive F1 score reflecting its balanced precision and recall.

VI. Results and Discussion

The conducted research centered on evaluating a 1D Convolutional Neural Network (CNN) for its efficacy in classifying stress levels. The model's performance, powered by the SWELL dataset, was scrutinized against the backdrop of its deployment potential within a low-power, real-time microcontroller environment — a critical consideration for wearable stress management devices.

A. Model Performance

The model's architecture, characterized by its 1D CNN framework, showcased outstanding results, reflected in the training accuracy of 99.43% and a test accuracy of 99.42%. An F1 score of 0.9942 further accentuated the model's prowess, underscoring its precision and recall balance — a testament to its reliability in stress-level differentiation.

1) Accuracy and Loss Over Epochs: The consistently high accuracy levels affirm the model's reliability, suggesting its capability to effectively discern between varied stress states with minimal overfitting risk. The corresponding model accuracy and loss over epochs are depicted in Figures 6 and 7.

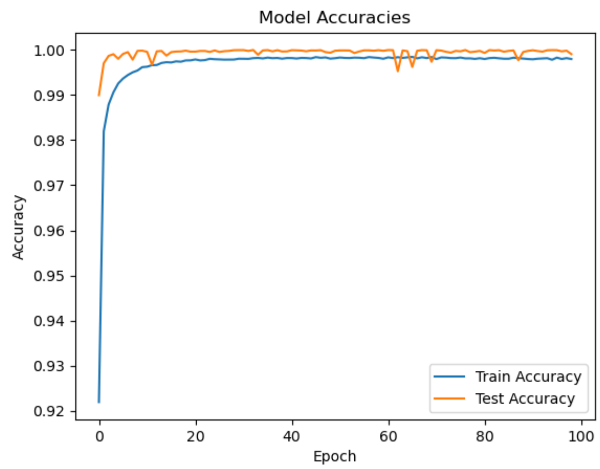

Fig. 6. Model accuracy evolution through the epochs, showcasing stability and convergence.

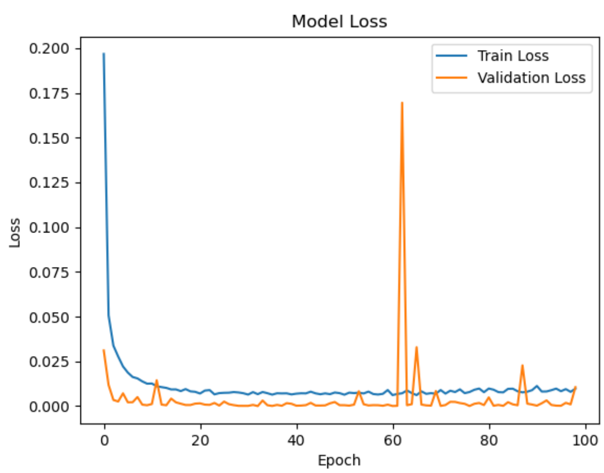

Fig. 7. Model loss reduction over time, indicating effective learning and optimization.

2) Confusion Matrix: The confusion matrix presented in Figure 8 offers insight into the model's classification accuracy across the various classes within the dataset, revealing a high degree of precision.

3) F1 Score Interpretation: The near-perfect F1 score indicates that the model not only accurately classifies stress levels but also maintains a high level of precision and recall balance, essential for imbalanced datasets where the repercussions of false negatives and false positives diverge significantly.

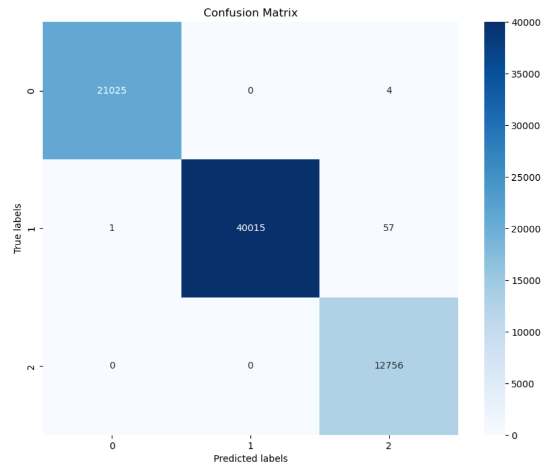

Fig. 8. Confusion matrix for stress-level classification, illustrating the model's predictive accuracy.

TABLE II
MODEL PERFORMANCE METRICS

Metric	Value
Training Accuracy	0.9943 (99.43%)
Testing Accuracy	0.9942 (99.42%)
F1 Score	0.9942

B. Feasibility of Real-Time Implementation

The compact and efficient nature of the proposed 1D CNN model aligns well with the prerequisites for real-time inferencing on low-power microcontrollers. Such alignment paves the way for its integration into wearable devices, optimizing for power efficiency and immediate user feedback.

C. Further Considerations and Enhancements

Looking forward, the successful integration of this model into a real-time wearable device will necessitate meticulous attention to computational constraints and power utilization, ensuring sustained operation and user convenience.

In addition to ongoing model optimization, future iterations may see the inclusion of a broader spectrum of physiological parameters, potentially enhancing the accuracy and predictive capability. Leveraging continuous learning mechanisms could introduce a layer of personalization, adapting the stress detection algorithm to individual user nuances, thereby elevating the intervention's impact.

VII. FUTURE WORK

A. Model Optimization and Web Development

To enhance the efficiency and generalizability of the model, particularly for real-time deployment on microcontrollers, we will employ dimensionality reduction techniques such as Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA). PCA will be used to reduce computational complexity while retaining essential information, and LDA will enhance class separation, crucial for accurately differentiating stress levels. Alongside these improvements, we are developing a web platform that will support users in practicing coherent breathing techniques, featuring functionalities like real-time monitoring, historical data logs, and coherence achievement indicators.

B. Quantifying Coherence for Model Enhancement

To enhance our model's capability in predicting and detecting the state of coherence using physiological features similar to those used for stress prediction, further studies are required. These studies will focus on quantifying the specific physiological markers associated with coherence, such as specific patterns in heart rate variability (HRV), respiratory rate, and perhaps even electrodermal activity (EDA).

C. Web Application Development

The front end of our web application is nearing completion. It is designed to offer user-friendly interfaces that enable users to monitor and improve their coherent breathing practices effectively. The upcoming phase will focus on developing the backend and server components, which are critical for processing data, managing user profiles, and providing interactive feedback. This development will ensure seamless integration with the wearable device, creating a comprehensive tool for stress management and physiological monitoring. For best practices in data privacy and security in wearable technologies, see [20].

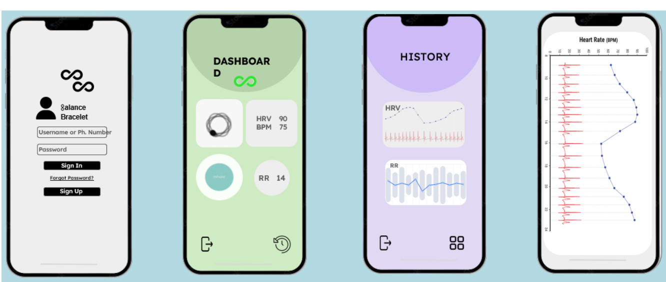

Fig. 9. Web Application Interface.

D. Testing and Evaluation Plan

1) Functional and Performance Testing: We plan to rigorously test each feature of the Balance Bracelet against defined requirements, assessing sensor reliability, placement accuracy, and the effectiveness of haptic feedback across different conditions and activities. Tests will also evaluate battery life, communication latency, and data accuracy to optimize performance.

2) Usability Testing: Usability testing will focus on the ease of use, learnability, and efficiency of task completion. We will conduct long-term wearability tests and utilize methods like A/B testing and the System Usability Scale (SUS) to gather user feedback. Longitudinal studies will also be carried out to determine the device's impact on stress levels and its durability over time.

E. Next Prototype Development

The next iteration of our wearable device, the Balance Bracelet, will incorporate several advanced components that enable comprehensive stress management and physiological monitoring:

- **Processor**: Acts as the central unit managing operations, sensor data collection, and network communications.
- **DSP Chip**: A dedicated digital signal processor that will perform complex signal processing tasks to derive respiratory rate from heart rate variability data.
- **PPG Sensor**: Utilized for continuous monitoring of blood volume changes to gather detailed HRV data.
- **Wi-Fi & BLE Chip**: Provides seamless connectivity options for data synchronization and real-time monitoring via both Wi-Fi and Bluetooth Low Energy.
- **Vibration Motor**: Delivers haptic feedback for user interaction, such as notifying when coherence is achieved or guiding breathing exercises.
- **OLED Display**: A small display to provide real-time feedback and visualizations of the user's HRV and respiratory rate.

These components will allow the implementation of on-device software, DSP, and ML inference, making the system capable of operating independently without the need for constant smartphone connectivity. This integration enhances user experience by providing immediate feedback and enables the device to function in various environments, promoting widespread usability.

F. Model Refinement and Deployment

Continuing development will focus on refining the model to ensure it is lightweight and efficient enough for integration into the wearable technology, aligning with the computational limits of the microcontroller used in our device.

G. Personalization and User Adaptation

Adapting the model to individual user profiles through continuous learning mechanisms will be crucial. This adaptation aims to enhance personalization, increase user engagement, and provide tailored stress management recommendations.

H. Testing and Validation

Comprehensive testing in real-world environments and extensive user studies will be conducted to validate the refined model's performance and usability, ensuring its effectiveness in daily applications.

I. Interdisciplinary Collaboration

Efforts will be made to foster interdisciplinary collaborations, addressing challenges such as ergonomic design, data privacy, and user interaction to ensure a holistic, user-centered approach in the development of our wearable stress management device.

These future initiatives are designed to advance the development of a sophisticated wearable device that not only effectively manages stress but also aligns with user preferences and needs, thereby contributing significantly to enhanced well-being.

ACKNOWLEDGMENT

The conception of this work was guided by Dr. Sari Roth-Roemer from the Barrow Neurological Institute. Special thanks to Dr. Troy McDaniel from Arizona State University and Trent Maruyama from the Barrow Neurological Institute for their valuable contributions and support.

REFERENCES

[1] T. M. Scott, P. L. Gerbarg, M. M. Silveri, G. H. Nielsen, L. Owen, M. Nyer, R. P. Brown, and C. C. Streeter, "Psychological function, iyengar yoga, and coherent breathing: A randomized controlled dosing study," *Journal of Psychiatric Practice*, vol. 25, no. 6, pp. 437–450, 2019.

[2] A. P. Association. (2023) Stress in america™ 2023: A nation grappling with psychological impacts of collective trauma. [Online]. Available: https://www.apa.org/news/press/releases/stress/2023

[3] B. S. McEwen, "Neurobiological and systemic effects of chronic stress," *Annual Review of Medicine*, vol. 68, pp. 141–156, 2017.

[4] G. Fincham, C. Strauss, J. Montero-Marin, and K. Cavanagh, "Effect of breathwork on stress and mental health: A meta-analysis of randomized controlled trials," *Scientific Reports*, vol. 13, no. 1, p. 432, 2023.

[5] M. A. Russo, D. M. Santarelli, and D. O'Rourke, "The physiological effects of slow breathing in the healthy human," *Breathe*, vol. 13, no. 4, pp. 298–309, 2017.

[6] P. Lehrer, *How does respiratory sinus arrhythmia (RSA) change with breathing rate and emotional state?* Biofeedback, 2013.

[7] "Heartrate+ coherence pro," 2020. [Online]. Available: https://heartrateplus.com/default.aspx

[8] "The benefits of coherent breathing with somnox," 2020. [Online]. Available: https://somnox.com/blog/coherent-breathing-somnox/

[9] M. Ma and D. Dorstyn, "The role of technology in clinical neuropsychology," *The Clinical Neuropsychologist*, vol. 32, no. 2, pp. 481–495, 2018.

[10] M. M. Cohen and S. Penman, "Integrative medicine and public health: A survey of stress management techniques," *Journal of Public Health Management and Practice*, vol. 21, pp. E20–E25, 2015.

[11] K. Giga and E. Zaluska, "The role of wearable devices in meeting the needs of cloud healthcare: current and future trends," *Healthcare Technology Letters*, vol. 4, no. 2, pp. 58–63, 2017.

[12] E. Murnane and S. Counts, "Opportunities and challenges for self-tracking in health," *Advances in Healthcare Informatics and Analytics*, pp. 143–165, 2018.

[13] "Respa: World's number one breathing sensor to boost workouts," 2020. [Online]. Available: https://www.respa.com

[14] "Oura ring: Advanced health tracking," 2020. [Online]. Available: https://ouraring.com

[15] "How does my garmin device track respiration rate?" 2020. [Online]. Available: https://support.garmin.com/en-US/?faq=2yEgS0Pax53UDqUH7q4WC6

[16] C.-H. I. Shih, N. Tomita, Y. X. Lukic, A. H. Reguera, E. Fleisch, and T. Kowatsch, "Breeze: Smartphone-based acoustic real-time detection of breathing phases for a gamified biofeedback breathing training," *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.*, vol. 3, no. 4, 2020. [Online]. Available: https://doi.org/10.1145/3369835

[17] J. Allen, "Photoplethysmography and its application in clinical physiological measurement," *Physiological Measurement*, vol. 28, no. 3, p. R1, 2007.

[18] A. V. Oppenheim and R. W. Schafer, *Discrete-Time Signal Processing*. Prentice Hall, 1999.

[19] S. Koldijk, M. Neerincx, and W. Kraaij, "Swell: Methodology for continuous in-the-wild stress detection," in *2014 IEEE International Conference on Healthcare Informatics*. IEEE, 2014, pp. 458–465.

[20] V. G. Motti and K. Caine, "Human factors considerations in the design of wearable devices," *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 59, no. 1, pp. 1820–1824, 2015.